# Research on Mobile Robot Path Planning Based on Artificial Potential Field and the Optimization of Artificial Potential Field

Hongyu Chen*

Dundee International Institute, Central South University, Changsha, China

*Corresponding author: 2617606@dundee.ac.uk

**Abstract.** Mobile robots play a significant role in enhancing the convenience of human life. Among the key research areas in mobile robotics, path planning is a central issue. Artificial Potential Field (APF), as a classic path planning algorithm, has received considerable attention. This paper introduces the principles and applications of path planning based on APF method. To address the issue of local minima, it analyzes existing approaches, including collision risk assessment and virtual target point methods. Furthermore, to tackle the problem of non-shortest path, the integration of APF with A-star algorithm, as proposed in the literature, is explored. Simulation experiments demonstrate that both improved methods achieve excellent results. This paper proposes an innovative improvement termed the "Contour Tracing Mode." Based on collision risk assessment, the contour tracing mode is introduced to avoid local minima. Additionally, a novel "Deviation Detection Formula" is proposed to determine whether the robot deviates from the original planned path. When deviation is detected, the integrated algorithm is reactivated to plan the shortest path. Finally, the paper discusses potential future developments of APF, providing references for further research.

**Keywords:** Artificial Potential Field; Path Planning; Virtual Target Points; A-star Algorithm; Contour Tracing Mode.

## 1. Introduction

Mobile robots are intelligent devices, capable of independently performing specific tasks in complex environments without relying on human intervention. Today, mobile robots are widely used in various specialized scenarios, such as entertainment, healthcare, mining, emergency response, teaching, defense, aerospace, farming, and beyond [1]. Since the outbreak of COVID-19 in 2020, mobile robots have become increasingly significant due to their ability to reduce the risk of virus transmission and enhance efficiency in contactless material delivery [2]. With the advancement of technology, the development of mobile robot automation can significantly improve human life. This is particularly true in extreme environments or unexpected real-world situations where certain conditions make it unsafe or inefficient for humans to work. In such cases, mobile robots are required to replace humans in completing critical designated tasks. Path planning is a key technology in robotics research and serves as the foundation for ensuring that robots can successfully complete designed tasks [3]. Therefore, how to effectively plan the path of a mobile robot—specifically, how to enable a mobile robot to autonomously determine an appropriate route in a specific working environment, move from the starting point to the target point, and avoid collisions with obstacles—is a critical issue that requires careful consideration and resolution. To address this problem, academic community has proposed various path planning algorithms, such as Depth-First Search (DFS), Breadth-First Search (BFS), Dijkstra's algorithm, Ant Colony Optimization (ACO), and Artificial Potential Field (APF), among others [4-6]. This paper focuses on an in-depth exploration of a well-known algorithm, Artificial Potential Field (APF). Due to its simplicity, concise structure, and ability to generate smooth paths, APF has been widely applied in obstacle avoidance and path planning for robots [7]. Whether it is aerial vehicles, ground-based robots, or waterborne vessels, APF can serve as a primary approach for their path planning tasks. Therefore, researchers can solve the path planning challenges of intelligent mobile robots to a certain extent by studying APF. However, APF still has some limitations. One issue is the local minima problem [8]. Local minima problem is where the resultant force generated by the target point and obstacles becomes zero, causing the robot to move within a region without progressing, ultimately becoming trapped and unable to reach the target point. Another challenge is when obstacles are too close to the target point, causing the repulsive force to exceed the attractive force as robot approaches the target point, leaving the robot always at a certain distance from the target point and unable to reach it. Additionally, the performance of APF in dynamic environments for obstacle avoidance is not ideal, highlighting the need for further improvements [9].

This paper aims to systematically introduce the fundamental principles of traditional APF and its extensive applications in the field of mobile robotics, while addressing three key issues associated with the method. The first one is local minima problem. This paper adopts the virtual target point method proposed in existing literature, which effectively enables robots to escape local minima by disrupting the force equilibrium state [10]. The second issue is path non-shortest problem. Some studies have addressed this by integrating APF with A-star algorithm, leveraging the global search capability of A-star algorithm to significantly shorten the planned path and enhance the mobility efficiency of robots [11]. The last problem arises in scenarios involving moving obstacles, where the robot may fail to avoid them in time. This paper analyzes and reflects on these challenges. Through the analysis of simulation results, it is demonstrated that the first two methods can effectively solve the respective problems associated with APF.

To further improve APF, this paper innovatively proposes new enhancement strategies: the “Contour Tracing Mode” and the “Deviation Detection Formula”. The “Contour Tracing Mode” is designed to solve the problem of local minima, while the “Deviation Detection Formula” aims to restart the integrated algorithm, optimizing its performance under special circumstance. Finally, this paper discusses and reflects on the future development directions and potential of APF.

## 2. Traditional Artificial Potential Field Path Planning

### 2.1. Principles of APF

APF was first mentioned by Khatib [6]. Khatib introduced the concept of potential fields from physics into the problem of obstacle avoidance for robotic arms and mobile robots. In this method, the target point is treated as an attractive source, while the obstacles are treated as repulsive sources, thereby constructing virtual attractive and repulsive potential fields. The attractive potential field and repulsive potential field exert an attractive force and a repulsive force on the robot, respectively. Both the attractive and repulsive fields are modeled as functions of the distance between the robot’s current position to the target point.

The attractive potential field can be expressed as:

$$U_{x_d}(x) = \frac{1}{2}k(x - x_d)^2 \tag{1}$$

The repulsive potential field can be expressed as:

$$U_o = \begin{cases} \frac{1}{2}\eta(\frac{1}{\rho} - \frac{1}{\rho_0})^2 \ (if\ \rho \le \rho_0) \\ 0 \ (if\ \rho > \rho_0) \end{cases} \tag{2}$$

The attractive potential force can be expressed as:

$$F = -k(x - x_d) \tag{3}$$

The repulsive potential force can be expressed as:

$$F_o = \begin{cases} \eta(\frac{1}{\rho} - \frac{1}{\rho_0})\frac{1}{\rho^2} \ (if\ \rho \le \rho_0) \\ 0 \ (if\ \rho > \rho_0) \end{cases} \tag{4}$$

In the equations, $x$ represents the current position of the robot, and $x_d$ the position of the target point. These equations also use $\rho$ to represent the shortest distance between the robot and the obstacle, $\rho_0$ to represent the maximum effective range of the repulsive field, k to represent the proportional constant for the attractive force, $\eta$ to represent the proportional constant for the repulsive force [6]. The resultant force is the vector sum of the attractive and repulsive forces. Under the influence of the resultant force, the robot moves approximately toward the target point while effectively avoiding obstacles, forming a smooth path that leads to the target point.

This illustrates the simplicity of APF. By simplifying the real-world scenario into a physical model and conducting force analysis, the robot's obstacle-avoiding path can be determined.

### 2.2. Applications of APF

APF has been widely used in various robotic systems. Drones, offering advantages such as high flexibility, low cost, environmental friendliness, and energy efficiency, have become increasingly prevalent in the logistics industry and effective path planning for drones is crucial as it significantly impacts distribution speed, cost reduction, and operational efficiency [12]. APF is highly effective for aerial path planning of drones. According to the research report by Alfian Ma'arif, although APF has certain limitations, it can still provide effective real-time guidance, navigation and obstacle avoidance for drones [13]. With subsequent improvements, the method has achieved significant results, successfully guiding drones to their target positions in numerous tests [13]. This demonstrates that APF is a practical and feasible approach for drones' path planning. Moreover, the method offers significant potential for improvement, enabling it to achieve even more optional results. Autonomous driving is a popular topic in modern vehicle technology and effective path planning is one of the key challenges currently faced in this field [14]. APF is effective in addressing path planning for static vehicles but requires further improvements for dynamic vehicle path planning [15]. In real-world scenarios with complex and dynamic road conditions, APF has certain limitations. However, it can effectively guide vehicles to their destinations in simple, static environments. As such, this method can serve as a foundational approach for autonomous driving applications, with modifications tailored to specific situations to achieve desired outcomes. A modified version of APF, known as the model predictive artificial potential field (MPAPF), has proven effective in complex maritime path planning, particularly in collision avoidance for ships [16]. This demonstrates that APF can serve as a significant approach to path planning for mobile robots across various environments, whether on water, land, or in the air. With appropriate modifications, this method can be further adapted to accommodate more complex and specific scenarios.

## 3. Optimization of Artificial Potential Field

From the aforementioned cases, it is evident that while APF can be applied to the path planning of many models, there are still numerous aspects that require further optimization.

### 3.1. Local Minima Problem

#### 3.1.1 Local Minima Problem Analysis

By analyzing the attractive force equation (3) and repulsive equation (4) of APF, a straightforward issue becomes apparent: when an obstacle is located between the robot and the target point, both $\rho$ and $(x - x_d)$ decrease as the robot approaches the obstacle. As a result, the repulsive force increases while the attractive force diminishes, potentially leading to a scenario where the repulsive force equals or exceeds the attractive force. This can cause the net force on the robot to become zero or deviate from the direction of the target, rendering the target point unreachable. In Hao's 2023 study on UAV collision avoidance, he categorized this type of local optimum issue into two distinct cases [10]:

The first case occurs when the UAV reaches a state of force equilibrium before arriving at the target point, with the obstacle positioned between the UAV and the target, as illustrated in Fig. 1:

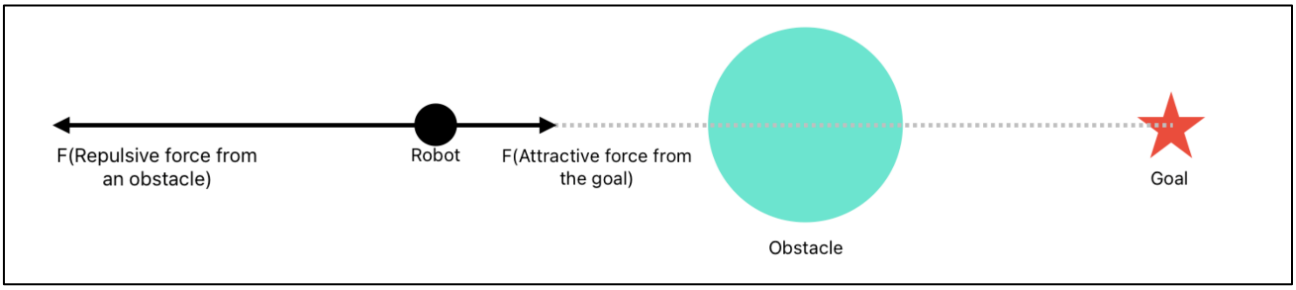


**Fig. 1** The obstacle exists between the UAV and the target point

The second case also arises when the UAV reaches a state of force equilibrium before arriving at the target point, but the obstacle is not located between the UAV and the target. In this scenario, the three are not collinear, as depicted in Fig. 2:

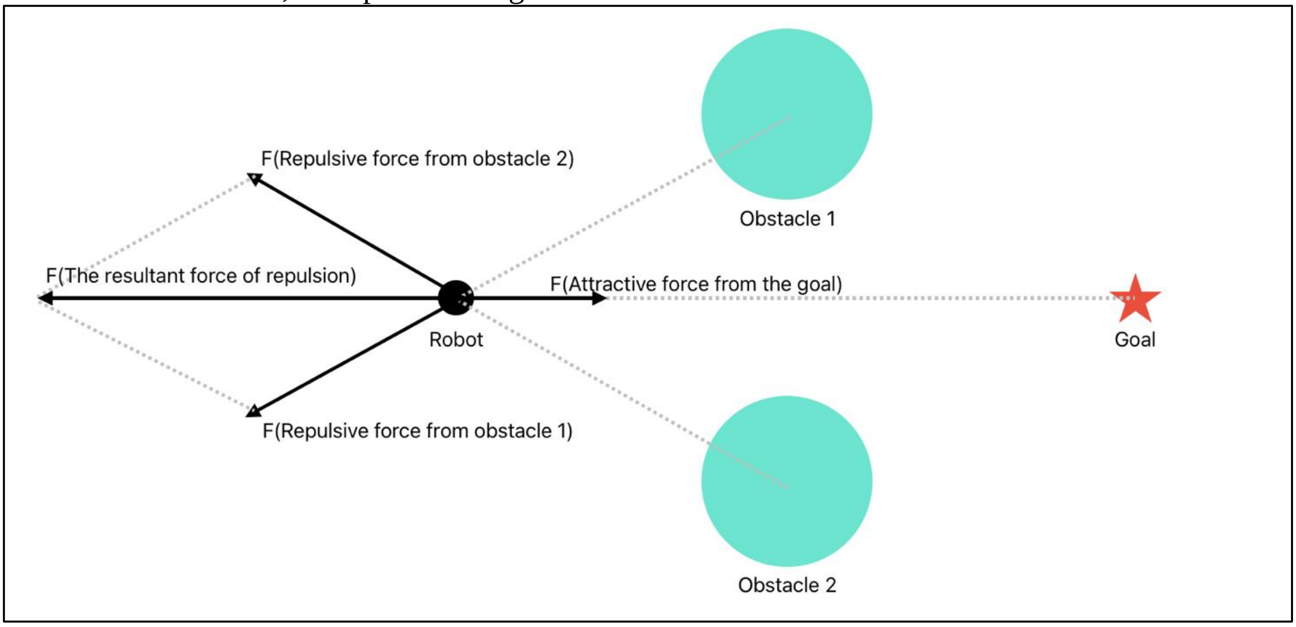


**Fig. 2** The obstacle does not exist between the UAV and the target point

### 3.1.2 Introduction of Virtual Target Point

To solve such situations, the referenced research proposed a collision risk judgment method and introduced the concept of virtual target points [10,17]. Collision risk judgment is used to evaluate whether the UAV is at risk of collision under these local minima conditions. When a collision risk is identified, a virtual target point is introduced at an appropriate location. The virtual target point is then evaluated to ensure the selection of the most suitable point. Both the target point and the virtual target point generate attractive forces on the UAV [10,17]. By continuously performing collision risk judgment, setting appropriate virtual target points, navigating towards these points, and iterating this process, the UAV can effectively avoid obstacles along its path. In addition, this research introduced three further improvements based on collision risk judgement and virtual target points. First one is virtual target point evaluation: selecting the optimal position for the virtual target point. The second one is incorporating obstacle boundary angles: adjusting the UAV's turning angle by considering the boundary angles of obstacles. The third one is adaptive step size: enhancing the method by introducing dynamic adjustments to the UAV's movement step size. With these enhancements, this research proposed the algorithm (referred to as IM-APF) [10].

### 3.1.3 Simulation experiment and result analysis

The reference research conducted three sets of simulation experiments to compare the IM-APF with the traditional APF (referred to as T-APF) and an improved version of APF from another reference (referred to as B-APF) [10,18]. The B-APF incorporates improvements solely using virtual target points and there are some differences in the underlying principles. These experiments specifically focused on addressing the issue of local minima. In the simulation experiments, the three algorithms guided the robot from a starting point to a target point respectively. The experiments were divided into three scenarios, as illustrated in Fig. 3, Fig. 4, and Fig. 5. In each experimental scenario, the starting point and the target point were fixed, while several obstacles were randomly placed between them. The distribution of obstacles in each scenario was designed to create local minimum situations. By testing whether the robot could successfully navigate around the obstacles under different algorithms, experimental conclusions were drawn.

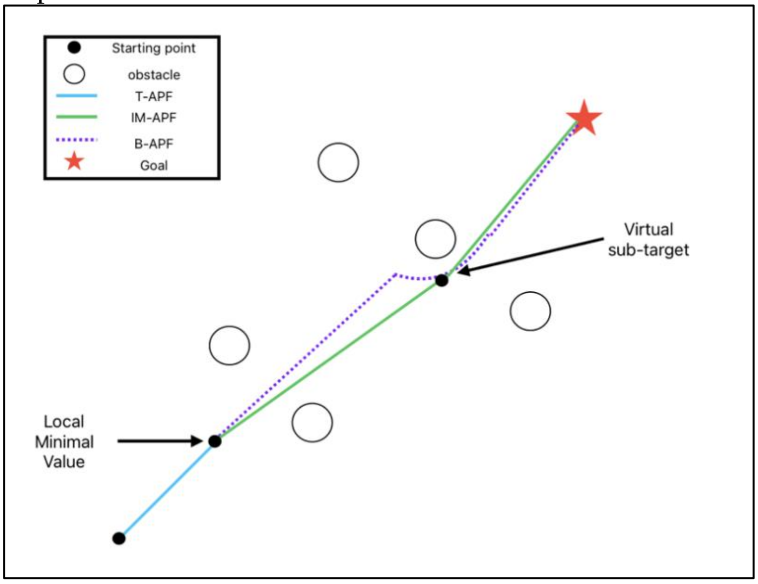


**Fig. 3** Simulation experiment scenario 1

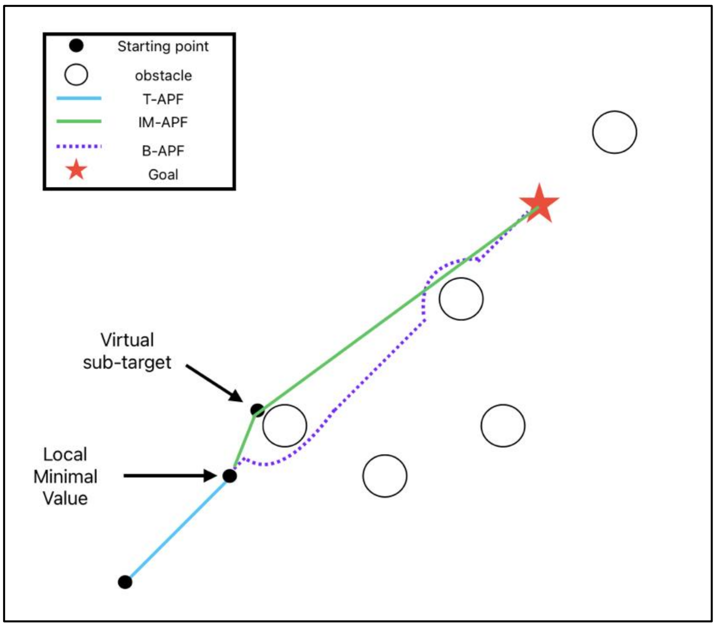


**Fig. 4** Simulation experiment scenario 2

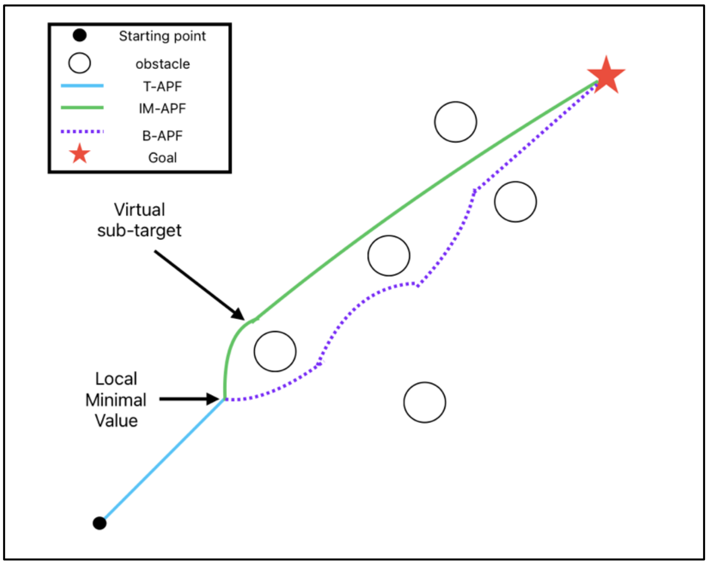


**Fig. 5** Simulation experiment scenario 3

The experiments recorded data on energy consumption, path length, and the iteration number for each algorithm across the three scenarios. As shown in Table 1, these metrics were used to evaluate and compare the performance of the algorithms under different conditions.

**Table 1.** The data of three scenarios in the simulation experiment

| Scenarios | Algorithm | Energy Consumption[kJ] | Path Length[m] | Iteration Number [N] |
|---|---|---|---|---|
| | T-APF | - | - | - |
| Scenario1 | B-APF | 35.67 | 34.1 | 342 |
| | IM-APF | 23.7 | 33.83 | 200 |
| | T-APF | - | - | - |
| Scenario2 | B-APF | 31.27 | 27.2 | 273 |
| | IM-APF | 21.1 | 27.06 | 156 |
| | T-APF | - | - | - |
| Scenario3 | B-APF | 36.18 | 35.8 | 359 |
| | IM-APF | 24.01 | 35.45 | 201 |

The experimental results indicate that both the B-APF and the IM-APF, which utilize virtual target points, effectively resolve the local minima issue of APF. Among them, the IM-APF outperforms B-APF in terms of lower energy consumption, shorter path length, and fewer iterations, demonstrating superior performance [10].

### 3.1.4 Local Minima Criterion and Virtual Target Point

In another reference on autonomous driving path planning, virtual target point is also proposed by Li et al. [19]. In this research on vehicle path planning, Li et al. discussed the local minima problem of APF, as well as the criteria for identifying U-shaped obstacle environments, as proposed by Xie et al. in another reference:

$$\left|F_{att} + \textstyle\sum_{j=1}^{n} F_{rep,j}\right| < \varepsilon \tag{5}$$

$$|x - x_a| < \alpha s_a \tag{6}$$

These equations use $F_{att}$ to represent the attractive force from the target point, $F_{rep}$ to represent the repulsive force from obstacles, $j$ to represent the number of obstacles, $\varepsilon$ to represent a small positive number, $x_a$ to represent a certain position in the motion of the vehicle, $s_a$ to represent the total distance travelled by the robot from position $x_a$ to the current position $x$ during the process [20]. In simple terms, these two equations are used for different criteria: one determines the state based on the magnitude of the resultant force, while the other evaluates the relationship between displacement and the total distance travelled. If either of the two equations is met, it can be concluded that the robot has fallen into a local minimum point. The conditions defined by these equations allow for a more accurate determination of whether the robot has fallen into a local minimum. This enables timely intervention to address the situation, preventing the robot from oscillating back and forth unnecessarily, thereby reducing time and energy consumption. In the aforementioned references, when the local minimum determination criterion is met, the authors, Li et al., introduce the concept of virtual target points. Unlike the virtual target points proposed by Hao, Li introduced a different approach where the gravitational field of the ultimate target point is temporarily ignored once the virtual target point is generated. This adjustment remains in effect until the robot successfully reaches the virtual target point, effectively preventing the robot from becoming trapped in local minima [19]. The position of the virtual target point and its generated attractive potential field can be expressed by the following four equations:

$$L_1 = \lambda a \tag{7}$$

$$L_2 = \mu b \tag{8}$$

$$L = \sqrt{{L_1}^2 + {L_2}^2} \tag{9}$$

These equations use $L_1$, $L_2$ and $L$ to represent the horizontal distance, vertical distance and Euclidean distance from the virtual target point to the obstacle respectively. These equations also use $a$ and $b$ to represent the length and width of the obstacle's dynamic model, $\lambda$ and $\mu$ to represent the distance expansion coefficients [19]. By adjusting $\lambda$ and $\mu$ according to the risk level posed by the obstacle, safe position for virtual target point can be determined.

$$U_{vir} = k_{vir}\sqrt{|x - x_0 - L|^2 + |y - y_0|^2} \tag{10}$$

This equation uses $k_{vir}$ to represent the potential energy increment coefficient of the virtual target point, $x$ and $y$ to represent the current coordinates of the robot, $x_0$ and $y_0$ to represent the coordinates of the virtual target point.

It can be observed that in addressing the local minima problem of APF, identifying local minima scenarios, conducting collision risk judgment, and introducing virtual target points effectively resolve this issue. Moreover, by reasonably determining the coordinates of the virtual target points, specifically through the appropriate adjustment of $\lambda$ and $\mu$, the robot can reach the ultimate target point more efficiently and effectively.

### 3.2. Path non-shortest problem

#### 3.2.1 Path non-shortest problem Analysis

The path generated by APF is determined by the combined effect of the attractive force from the target point and the repulsive force from obstacles. Consequently, it does not necessarily represent the shortest path from the starting point to the target point, which may result in unnecessary costs and energy consumption.

#### 3.2.2 Fusion Algorithm of Artificial Potential Field and A-star Algorithm

According to the study by Ju et al., while APF is more effective than the A-star algorithm in handling dynamic obstacles, the paths generated by APF are significantly longer than those generated by the A-star algorithm [11]. To address this, Ju et al. proposed a fusion algorithm that integrates APF with the A-star algorithm. This integration ensures successful path planning under dynamic conditions while also reducing the overall path length. Therefore, this fusion algorithm can be utilized for robot path planning [11]. The specific fusion algorithm is as follows:

Step 1: Use the A-star algorithm to generate an initial path based on map information, the starting point, the target point and obstacles. The key points along the path are recorded in a set of waypoints, which will serve as a reference for the subsequent fusion algorithm.

Step 2: Using the robot's current position as the center, define a circle with a specified radius to detect whether any waypoints lie within the circle. If waypoints are present, both the waypoints and the target point generate attractive forces on the robot. If no waypoints are detected, only the attractive force of the target point is considered. The repulsive force from obstacles is calculated in the same way as in the traditional APF. Under the combined effect of the attractive and repulsive forces, the robot calculates an appropriate step size based on the resultant force direction and the actual environmental conditions, determining the position of the next point.

Step 3: By continuously repeating the process described in Step 2, the sequentially generated points are connected to form a complete path.

In other words, by integrating APF into the path initially planned by the A-star algorithm, the attractive and repulsive forces of APF are applied to the robot. This ensures that the robot follows a path derived from the heuristic algorithm while also enabling it to easily avoid dynamic obstacles under the influence of the repulsive forces.

### 3.2.3 Experimental Results and Analysis

To evaluate the feasibility and effectiveness of the proposed fusion algorithm, this study conducted experimental comparisons between the fusion algorithm and several other methods, including A-star algorithm, APF, and two alternative algorithms that also integrate A-star algorithm and APF but use different fusion approaches. These two alternative fusion algorithms are referred to as R1 and R2 [21,22].

The experiment was conducted using MATLAB software to construct a 15 × 15 grid map. The start and goal coordinates were set to (1, 1) and (11, 11), respectively, with 50 obstacles randomly placed on the map. A representation similar to Fig. 6 was used for visualization:

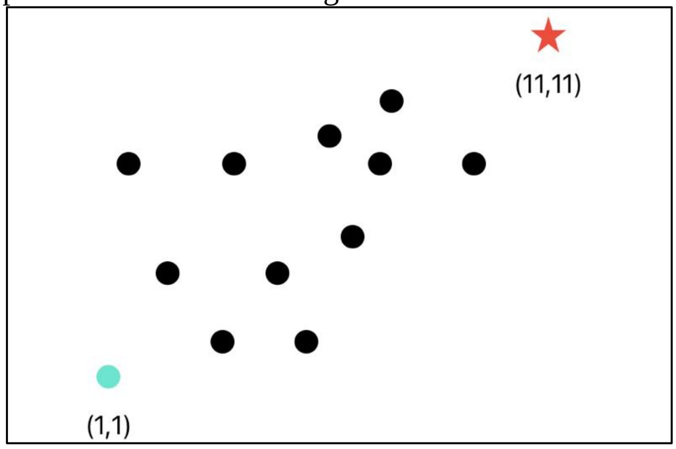


**Fig. 6** 15 × 15 simulated map

Each algorithm generates a path from (1, 1) to (11, 11) [20]. The experiment recorded the path length and computation time for each algorithm. The evaluation was performed by comparing the generated path lengths and computation times across the different algorithms. The experimental data are shown in Table 2:

**Table 2.** Data from the five algorithms in the experiment

| | A-star | APF | R1 | R2 | Fusion algorithm |
|---|---|---|---|---|---|
| Path length(m) | 17.7279 | 15.0897 | 15.8056 | 15.8767 | 14.2182 |
| Processing time(s) | 2.128 | 0.738 | 2.665 | 2.391 | 3.318 |

The experimental results demonstrate that the proposed fusion algorithm produces a path that is nearly 6% shorter than the one generated by APF. Compared to the other algorithms tested in the experiment, the path length is reduced by 3.46%, 10.04%, and 10.45%, respectively [20]. However, due to the higher number of path points and the complexity of the algorithm, the computation time of the fusion algorithm is slightly longer than that of the other algorithms.

This demonstrates that the fusion algorithm combining A-star algorithm and APF proposed by Ju et al. effectively solves the issue of excessively long paths generated by APF.

The two improvement methods discussed above both successfully address the existing issues to a significant extent. The virtual target point approach resolves the local minimum problem by breaking the force balance, effectively eliminating the conditions under which the problem arises and enabling the robot to continue moving forward. Meanwhile, the fusion algorithm incorporates the global path-planning capability of A-star algorithm, resulting in shorter final paths. By leveraging the strengths of different algorithms, it effectively minimizes the length of the planned path.

# 4. Discussion and Analysis

## 4.1. Contour Tracing Mode

This paper argues that, based on the methods above, the local minima problem can be further explored from new perspectives, such as edge-following progression. Robots with APF are prone to the problem of local minima and collision risk judgment [16] and the local minima criterion [19] provide excellent foundational tools and should be preserved. Building on these foundations, this paper proposes tackling the problem from the perspective of navigating around obstacles while moving closer to the target. Specifically, the focus shifts to utilizing the outer contour of obstacles, guiding the robot to advance along the edges of obstacles. The first essential step in this approach is collision risk judgment:

Step 1: When the local minima criterion formula is satisfied, initiate collision risk judgment. If the obstacle is not located within the direct line between the robot and the target point and the traversable distance exceeds the robot's width, the repulsive force field is deactivated, allowing the robot to proceed without interference. However, if the obstacle lies along the direct line, and deactivating the repulsive force field would result in a collision risk, the “contour tracing mode” is activated.

Step 2: Continuing with the first step, when the robot is not in this mode, it ignores repulsive forces that pose no collision risk directly and continues to move forward until it encounters new local minima or reaches the target point. In contour tracing mode, both the repulsive and attractive force fields are temporarily disabled. The robot scans the outer contour of the obstacle and generates an “obstacle influence contour” by extending outward from the obstacle's boundary to provide directional buffering. The robot then advances along this “obstacle influence contour”, using heuristic calculations based on A-star algorithm [23] to select a direction closer to the target point. If the obstacle's complexity results in too excessive data, a local scan is performed, and adjustments are made dynamically as the robot progresses.

Step 3: In contour tracing mode, as the robot advances, collision risk judgment is reassessed when the obstacle no longer lies on the direct line between the robot and the target point (as shown in Fig. 7). If the traversable width of the direct line exceeds the robot's width, the robot exits edge-following mode, disregards the repulsive force field of the bypassed obstacle, and restores the attractive force field of the target point. If the width is less than the robot's width, edge-following mode continues, and the robot proceeds along the “obstacle influence contour” until a sufficiently wide path is identified. Theoretically, the expected trajectory in edge-following mode is illustrated in Fig. 7:

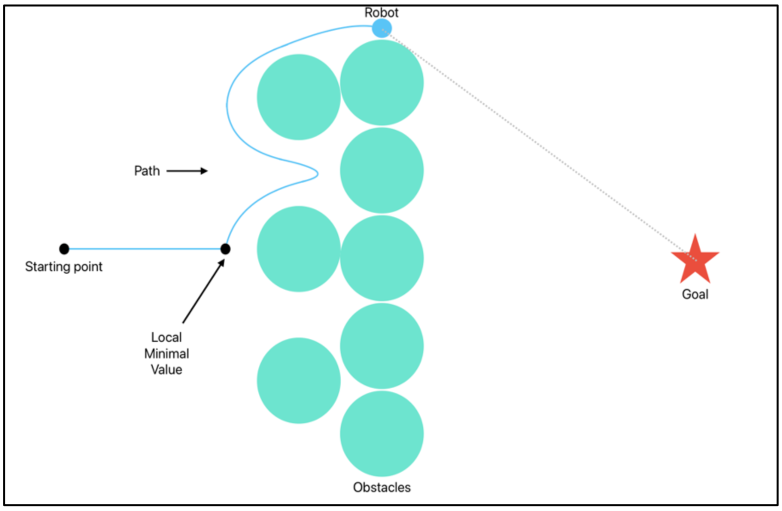


**Fig. 7** Robot bypassing obstacles in contour tracing mode

The contour tracing mode effectively solves the local minima problem inherent in APF. Its advantages include:

Simplicity: The principle is straightforward, requiring no significant algorithmic complexity.

High Safety: It maintains a safe distance from obstacles.

Flexibility: The path can be dynamically adjusted based on the contours of obstacles and the surrounding environment.

However, it also has several drawbacks:

Inefficient Paths: Irregular obstacle surfaces may lead to ineffective paths and overly long trajectories (as illustrated in Fig. 7).

Poor Performance with Scattered Obstacles: The method may struggle with dispersed obstacles, potentially failing to lead robot to the target point.

High Computational Complexity: The calculations involved are quite complicated.

The "contour tracing mode" represents an exploratory direction and requires further optimization and refinement.

### 4.2. Deviation Detection Formula

Regarding the fusion algorithm combining APF and A-star algorithm [11], this paper identifies certain limitations. Specifically, when dynamic obstacles cause the robot to deviate significantly from its original path, the search area may lack available waypoints, leaving subsequent path planning solely dependent on the attractive force of the target point. This behavior resembles that of traditional APF.

The issue becomes particularly pronounced when dynamic obstacles move irregularly. The robot, influenced by strong repulsive forces, deviates from the initial path planned by A-star algorithm. After avoiding the obstacles, it is guided only by the target point's attractive force, leading to suboptimal path planning. As shown in Fig. 8, the robot is disrupted by a moving obstacle and diverted from Point 1 to Point 2, resulting in a significant deviation from its original path.

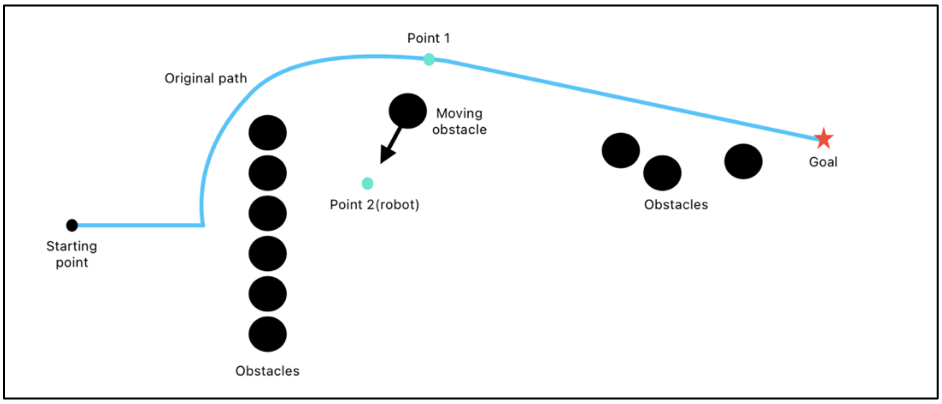


**Fig. 8** The robot deviates far from the original planned path

To optimize the shortest path to the target point, improvements can be made to the original fusion algorithm by introducing a "deviation detection formula" to enhance its functionality. When the robot deviates from the original path, the "deviation detection formula" triggers a return to the first step of the fusion algorithm, enabling A-star algorithm to replan the shortest path and determine key waypoints.

The robot continuously monitors nearby waypoints and determines its next position based on the resultant force direction and the surrounding environment. This iterative process repeats the initial steps of the fusion algorithm, ensuring the robot retains the algorithm's hybrid characteristics during subsequent movements. The formula for determining deviation from the original path is as follows:

$$|x - x_i| > \alpha \tag{11}$$

This equation uses $x$ to represent the current position of the robot, $i$ to represent any waypoint in the original waypoint collection, $x_i$ to represent the position of this waypoint, $\alpha$ to represent a reasonable distance. This equation indicates that when the distance between the robot's current position and the nearest waypoint on the original path exceeds $\alpha$, it is determined that the robot has deviated from the path. This triggers the replanning process to calculate the shortest path at the moment using A-star algorithm.

### 4.3. Dynamic Obstacles and Realistic Environment

In scenarios with prolonged absence of obstacles, the robot's speed may become excessively high. If a dynamic obstacle suddenly appears in the path, insufficient buffering distance could result in a failure to avoid the obstacle, leading to a serious collision. To solve this, intelligent algorithms must continuously monitor the surrounding environment in real time, predict potential sudden obstacles, and proactively reduce speed to ensure safety.

Additionally, it is crucial to establish a reasonable maximum speed limit to balance both safety and time efficiency. In practice, path planning becomes significantly more complex due to factors such as dynamic obstacles, unpredictable interferences, and irregular terrains. Therefore, APF must be improved or integrated with advanced algorithms to effectively handle these complex scenarios.

## 5. Conclusion

Based on the research of APF in mobile robot path planning, this paper provides an overview of its fundamental principles, practical applications, and current limitations. APF operates on the principle of generating attractive and repulsive forces through potential fields, offering highly efficient obstacle avoidance capabilities. It has demonstrated significant advantages in various domains, including aerial drone navigation, autonomous ground vehicle driving, and maritime vessel guidance.

However, APF still faces challenges such as local minima, non-shortest path lengths, and limited adaptability to dynamic environments. To address the local minima problem, introducing collision risk judgment and virtual target points to disrupt force balance can effectively resolve the issue. Additionally, exploring the fusion of APF with the A-star algorithm has proven beneficial. By leveraging the A* algorithm’s capability for global shortest path planning and integrating the strengths of both approaches through modifications, the problem of non-shortest path can be significantly alleviated. This enhances the efficiency of robot movement and reduces energy consumption.

Finally, this paper proposes a "contour tracing mode" based on APF, enhanced by collision risk judgment and the A-star algorithm, providing a novel improvement approach to APF. Furthermore, it addresses the limitations of the existing fusion algorithm combining APF and A-star algorithm by introducing a “deviation detection formula” to refine and strengthen the fusion algorithm. This modification enhances its applicability in special scenarios, improving its overall performance.

Current research on APF in dynamic environments, especially in real-world complex and unpredictable scenarios, still faces certain limitations. Future development of APF should focus on three key directions:

Integration with advanced path planning algorithms: combining APF with various advanced algorithms to leverage their respective strengths and address their weaknesses.

Enhanced real-time environment monitoring and risk prediction: strengthening the algorithm's capability to monitor the surrounding environment and predict potential hazards, thereby preventing unexpected collisions.

Improvement in intelligent decision-making algorithms: developing more autonomous decision-making capabilities for robots to enhance their ability to plan paths intelligently and adapt to special or unforeseen circumstances.

These directions aim to make the artificial potential field method more robust and effective in handling the complexities of real-world applications.

This paper offers a comprehensive exploration of the optimization of the artificial potential field method, aiding readers in understanding its underlying principles. It also encourages readers to contemplate future innovations and improvements to the artificial potential field method, fostering new ideas for advancing this approach. With continued research and improvement, APF is poised to play an increasingly significant role in solving path planning problems for mobile robots. It will provide robust support for advancing the intelligence and development of mobile robotics.

## Reference

[1] Patle B K, Pandey A, Parhi D R K, et al. A review: On path planning strategies for navigation of mobile robot. Defence Technology, 2019, 15(4): 582-606.

[2] Liu L, Wang X, Yang X, et al. Path planning techniques for mobile robots: Review and prospect. Expert Systems with Applications, 2023, 227: 120254.

[3] Li Y, Huang Z, Xie Y. Path planning of mobile robot based on improved genetic algorithm//2020 3rd International Conference on Electron Device and Mechanical Engineering (ICEDME). IEEE, 2020: 691-695.

[4] Dijkstra E W. A note on two problems in connexion with graphs//Edsger Wybe Dijkstra: his life, work, and legacy. 2022: 287-290.

[5] Dorigo M. Optimization, learning and natural algorithms. Ph. D. Thesis, Politecnico di Milano, 1992.

[6] Khatib O. Real-time obstacle avoidance for manipulators and mobile robots//Proceedings. 1985 IEEE international conference on robotics and automation. IEEE, 1985, 2: 500-505.

[7] Dian-Fu Z, Fu L. Research and development trend of path planning based on artificial potential field method. Computer Engineering & Science/Jisuanji Gongcheng yu Kexue, 2013, 35(6).

[8] Duhé J F, Victor S, Melchior P. Contributions on artificial potential field method for effective obstacle avoidance. Fractional Calculus and Applied Analysis, 2021, 24: 421-446.

[9] Fan X, Guo Y, Liu H, et al. Improved artificial potential field method applied for AUV path planning. Mathematical Problems in Engineering, 2020, 2020(1): 6523158.

[10] Hao G, Lv Q, Huang Z, et al. Uav path planning based on improved artificial potential field method. Aerospace, 2023, 10(6): 562.

[11] Ju C, Luo Q, Yan X. Path planning using artificial potential field method and A-star fusion algorithm//2020 global reliability and prognostics and health management (PHM-Shanghai). IEEE, 2020: 1-7.

[12] Li Y, Liu M, Jiang D. Application of unmanned aerial vehicles in logistics: a literature review. Sustainability, 2022, 14(21): 14473.

[13] Ma'Arif A, Rahmaniar W, Vera M A M, et al. Artificial potential field algorithm for obstacle avoidance in uav quadrotor for dynamic environment//2021 IEEE International Conference on Communication, Networks and Satellite (COMNETSAT). IEEE, 2021: 184-189.

[14] Parekh D, Poddar N, Rajpurkar A, et al. A review on autonomous vehicles: Progress, methods and challenges. Electronics, 2022, 11(14): 2162.

[15] Li Y, Yang W, Zhang X, et al. Research on automatic driving trajectory planning and tracking control based on improvement of the artificial potential field method. Sustainability, 2022, 14(19): 12131.

[16] He Z, Chu X, Liu C, et al. A novel model predictive artificial potential field based ship motion planning method considering COLREGs for complex encounter scenarios. ISA transactions, 2023, 134: 58-73.

[17] Feng S, Qian Y, Wang Y. Collision avoidance method of autonomous vehicle based on improved artificial potential field algorithm. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 2021, 235(14): 3416-3430.

[18] Hu Z, Xu B. Trajectory Planning of Improved Artificial Potential Field Method. Electronics Optics Control, 30(1): 38-41.

[19] Li X, Li G, Bian Z. Research on Autonomous Vehicle Path Planning Algorithm Based on Improved RRT* Algorithm and Artificial Potential Field Method. Sensors, 2024, 24(12): 3899.

[20] Xie C, Tao T, Li J. Research on path planning based on improved artificial potential field method. Scientific Insights and Discoveries Review, 2024, 3: 95-103.

[21] Lin B. Research on path planning of handling robot based on improved A* algorithm and artificial potential field method. Changan University, 2017.

[22] Xuan R. Research on Intelligent path Planning Based on Improved A* Algorithm and Artificial Potential Field Method. **'an University of Electronics and Technology, 2019.

[23] Hart P E, Nilsson N J, Raphael B. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 1968, 4(2): 100-107.